CLASSIFICATION and PREDICTION of WIND TUNNEL MACH NUMBER RESPONSES USING both COMPETITIVE and GAMMA NEURAL NETWORKS

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ABSTRACT

Recent research efforts have investigated the use of competitive neural networks to classify the Mach number responses of the 16 Foot Transonic Tunnel at NASA Langley Research Center, Hampton, Virginia. Control input and Mach-number response data from a 45 minute tunnel run were used for training and testing the neural network classifiers. The wind tunnel Mach number was varied from 0.4 to 1.3, covering most of the operational range of the facility. Control inputs, consisting of raise or lower commands of varying duration to the tunnel fan drive system, ranged from 0.25 seconds to 2.5 minutes. Prediction of the Mach number response for a specific class of responses was investigated using a recursive, gamma-memory neural network topology suited to system identification. The combination of classification using a competitive network , and prediction using a gamma network, provides increased accuracy in predicting the tunnel's Mach number response to a specific class of control inputs.

BACKGROUND

The 16-Foot Transonic Tunnel at the NASA Langley Research Center, Hampton, Virginia, is a closed circuit, single-return, continuous-flow, atmospheric tunnel with a Mach number capability from 0.20 to 1.30. When the tunnel began operation in November 1941, it had a circular test section that was 16 feet in diameter and maximum Mach number of 0.71. [Peddrew, 1981] Numerous upgrades to both the test section and drive system have expanded the test envelope of this facility. Currently, Mach numbers up to 1.05 are achieved using the tunnel main drive fans only. Mach numbers from 1.05 to 1.3 require the combination of test section plenum suction with the tunnel fans. The tunnel fans, 34 feet in diameter, are driven from 60 to 372 rpm by a 50 MW electric drive system. An air removal system using a 30 MW compressor and 10-Foot diameter butterfly valve provides test section plenum suction . At Mach numbers above 1.275, the 10-Foot valve is fully open and increases in Mach number are obtained from increased power to the tunnel main drive fans.

Some of the salient features of the Mach number dynamics of the 16 Foot Tunnel are:

- The nominal dynamics vary significantly over the operational range of the tunnel;
- The control input to the tunnel fan drive system is bang-zero-bang: (+1 raise, -1 lower, 0 maintain speed);
- There is transport lag (pure delay) that varies over the operational range;
- The dynamics can change dramatically at any given operating point due to test conditions (blockage);
- The test section Mach number computed from pressure measurements is noisy;
- Power consumption is significant: 20 MW @ Mach 0.7, 80 MW @ Mach 1.3.

INTRODUCTION

Earlier efforts investigated a recursive gamma-memory [DeVries and Principe, 1992] neural network architecture for system identification [Motter and Principe, 1994]. A single network was trained to predict the Mach number response of the wind tunnel for 40 sample periods into the future, based on an input-output history of ten samples. The network was trained using data from the entire operating range of the facility, and consequently tested over the same range. Results were encouraging, indicating that a single predictor could capture some of the dynamics of the tunnel response and predict the steady-state Mach number 40 samples into the future to within +/-0.001.

The focus of this effort was to investigate the use of competitive neural networks [Hertz, Krough, and Palmer] to classify the tunnel Mach number responses resulting from similar control inputs. Five competitive networks were trained to classify Mach number responses from a 45 minute tunnel run, shown in Figure 1, into 70 classes. A typical 50 point sample window with 20% control duration is also shown.

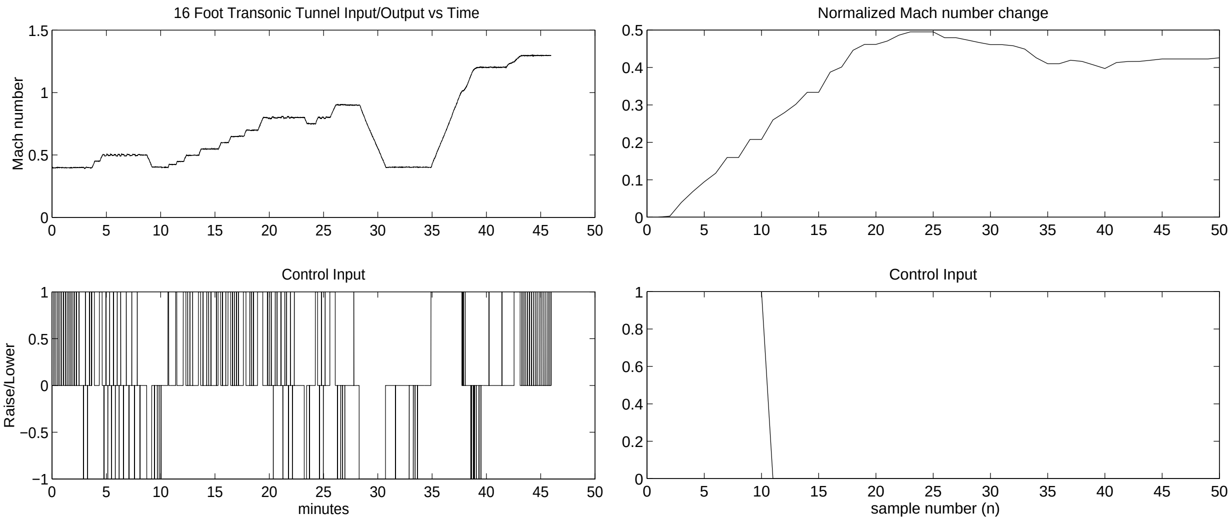

Figure 1. 16 Foot Transonic Tunnel Control Input and Mach Number Responses

CLASSIFICATION

Competitive networks were constructed to classify responses for data window lengths of both 10 and 50 samples. The classes of similar control inputs were identified by the duration of control input as a percentage of the data window length. These percentages were 100, 20, 2-6 and zero percent. The five networks represented the following combinations:

- 50 sample data window: 100, 20, and 2-6 % control duration;
- 10 sample data window: 100 and 0 % control duration.

The input-output data for the 50 sample data window, 20% control duration network, is shown in Figure 2. A competitive network was trained to classify the 50-point Mach number responses shown in Figure 2 into eight different classes. Also shown are the trained competitive network weights.

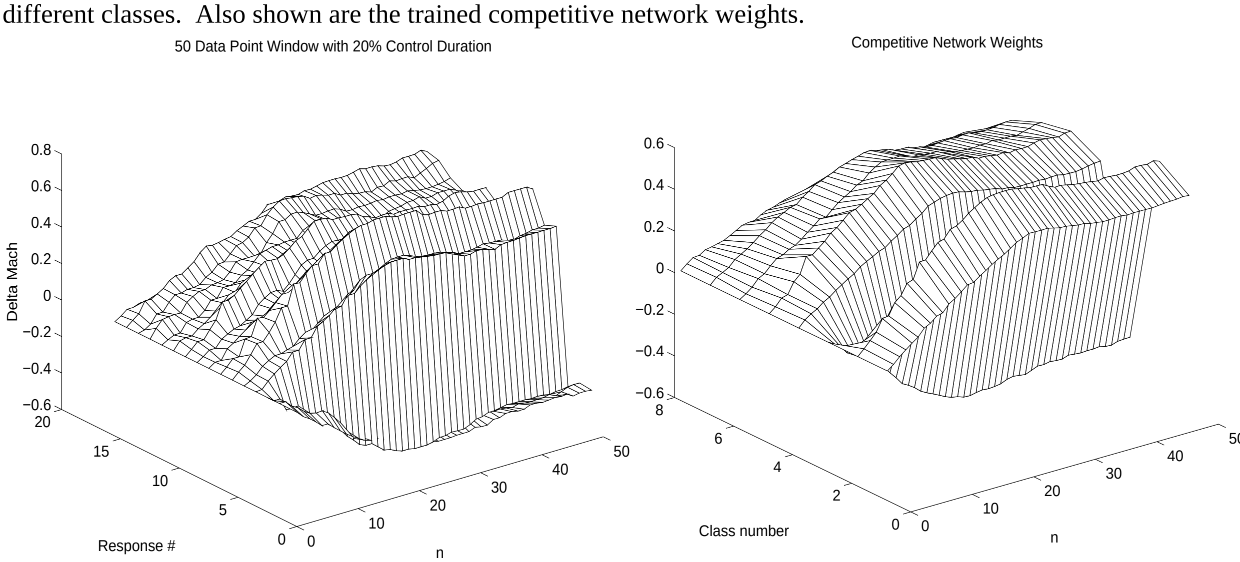

Figure 2. 50 sample data with 20% control duration and corresponding competitive network weights

The competitive network classified the responses shown on Figure 2 into eight different classes. A composite of each class was made by averaging each point in the data window over all members of a class. The composite representation of the eight classes is shown in Figure 3.

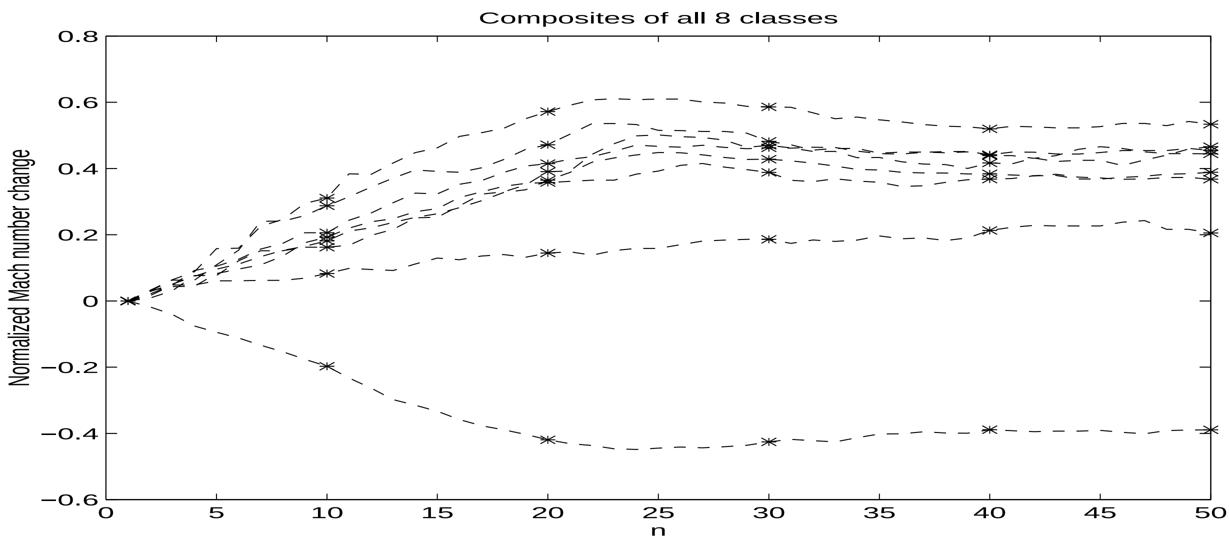

Figure 3. Eight classes from 50 point sample window with 20% control duration

Figure 4 shows the maximum and minimum values of each data point for two of the eight classes, along with both a composite and typical member of the class.

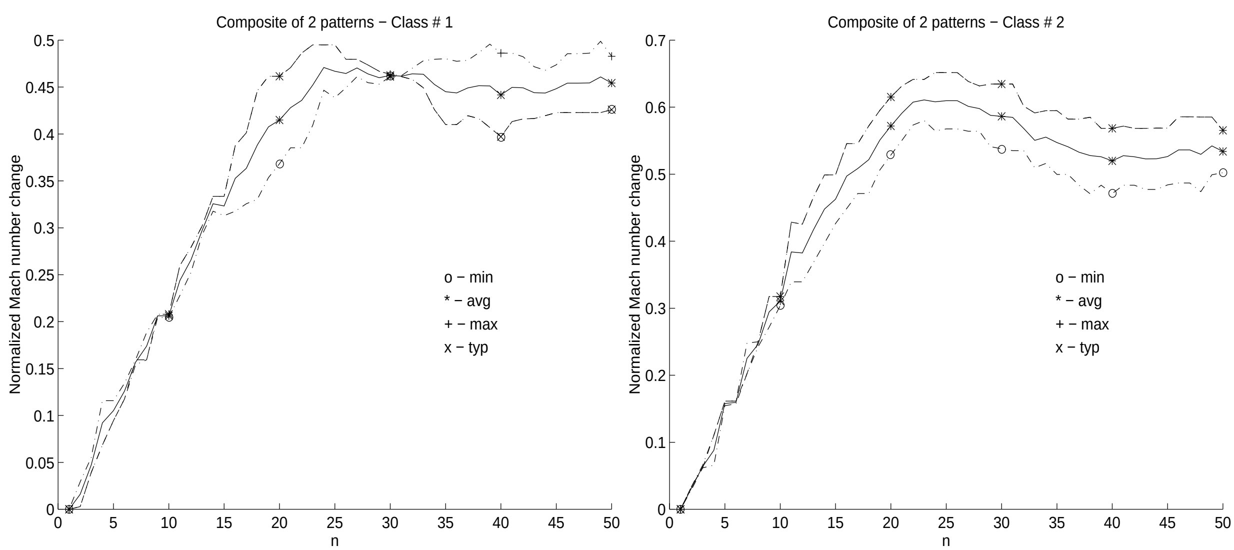

Figure 4. Characteristics of two of the eight classes

<u>PREDICTION</u>

A predictor was trained for each class identified by the competitive network. The predictor is initialized with the ten most recent values of the control input and Mach number response, and then predicts the next forty samples of the Mach number response based on zero control input. Details of both the architecture and training of the recursive, gamma-memory neural network predictor are described in [Motter and Principe, 1994]. Figure 5 shows the predictor output for several classes of the 50 point sample window, 20% control duration responses.

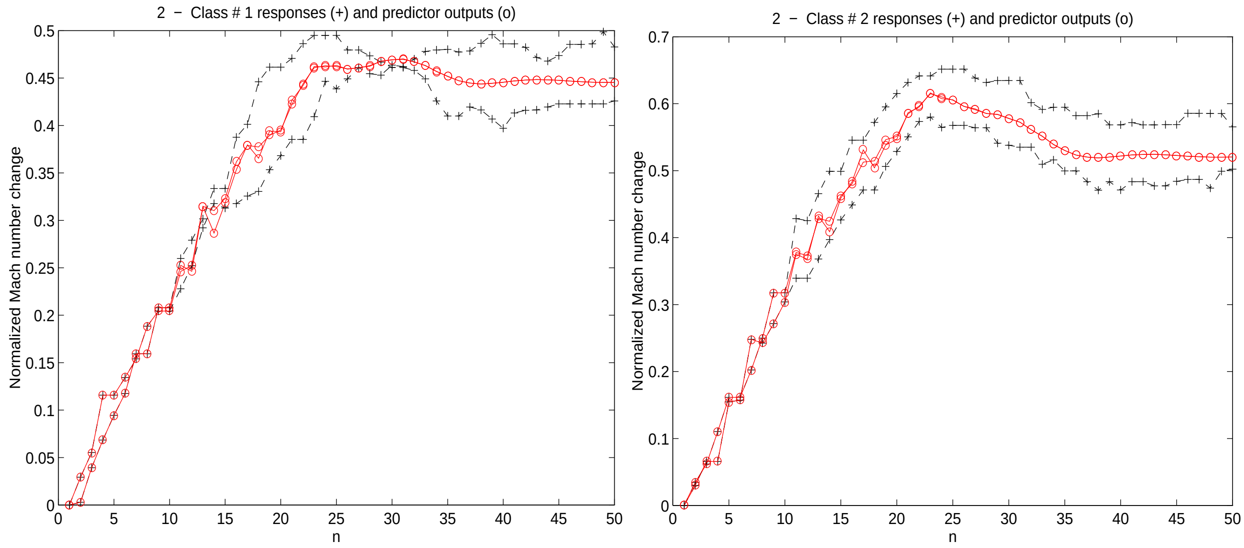

Figure 5. 40 Sample Prediction of Mach number responses for two different classes

CONCLUSION

The use of competitive networks to cluster the Mach number responses into classes provides a basis for developing a set of predictors which can more accurately predict the dynamics of the wind tunnel’s response. This is in contrast to previous results which used a single predictor, capable of accurately predicting the steady -state response while capturing only some of the general features of the dynamic response. Improved prediction results have been shown for the classes of Mach number responses associated with control inputs of 20% duration of the 50 point sample window as shown in Figure 2. Further work will attempt to identify the minimum number of classes to accurately predict the dynamics of the Mach number response for all control inputs of interest.

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